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An Intent Recognition Strategy for Transfemoral Amputee Ambulation Across Different Locomotion Modes

Aaron J. Young, *Student Member, IEEE*, Ann Simon, *Member, IEEE* and Levi J. Hargrove, *Member, IEEE*

Abstract—**Powered lower limb prostheses, capable of multiple locomotion modes, are being developed for transfemoral amputees. Current devices do not seamlessly transition between modes such as level walking, stairs and slopes. The purpose of this study was to develop an intent recognition system and test its performance across five different modes. A Dynamic Bayesian Network (DBN) was used for classification of neural and mechanical signals while four amputees completed a circuit containing level-walking, ramp ascent, ramp descent, stair ascent and stair descent. Our results indicate that transitional and steady-state stair steps had a high recognition rate (>99%), while ramp steps were significantly more difficult to classify (p<0.01) (13.7% error on transition steps and 1.3% on steady-state steps). With all five modes trained into the same system, the transitional error rate was 11.3%. Transitional error could be reduced by 31% by training the ramp ascent mode as level walking, and 92% by training both ramp ascent and descent as level walking. This is a viable solution when the level-walking mode can accommodate ramp modes which is currently the case with the ramp ascent. The high recognition rates for recognizing stairs shown in this study demonstrates the potential for an intent recognition system using neural information to allow amputees to naturally transition between locomotion modes on powered prostheses.**

I. Introduction

In the last decade, there have been large advances in lower limb prosthetic technology including onboard computers [1] and motorized joints [2, 3]. With more advanced componentry, these devices are better able to aid amputees on more difficult terrain allowing for reciprocal gait for stair ascent and descent [4]. To fully use these new capabilities, methods for transitioning between locomotion modes are necessary. Currently, transfemoral prosthesis users must press a button or perform a specific lower limb movement to signal to their prosthesis that they want to change between certain modes such as transitioning from walking to stair ascent. A smarter system might allow for these transitions to be automatic (no button press), seamless (no stopping) and natural (no unnatural user movements).

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A.J. Young is with the Center for Bionic Medicine at the Rehabilitation Institute of Chicago, Chicago, IL 60611 USA and with the Department of Biomedical Engineering at Northwestern University (phone: 312-238-2415; fax: 312-238-2081; e-mail: ajyoung@u.northwestern.edu).

A.M. Simon is with Center for Bionic Medicine at the Rehabilitation Institute of Chicago, Chicago, IL 60611 USA and with the Department of Physical Medicine and Rehabilitation at Northwestern University, Chicago, IL, 60611, USA (e-mail: annie-simon@northwestern.edu).

L.J. Hargrove, is with Center for Bionic Medicine at the Rehabilitation Institute of Chicago, Chicago, IL 60611 USA and with the Department of Physical Medicine and Rehabilitation at Northwestern University, Chicago, IL, 60611, USA (e-mail: l-hargrove@northwestern.edu).

To address these issues, intent recognition techniques using pattern recognition algorithms are being developed [5, 6]. One study [5] demonstrated high recognition rates using mechanical sensors within a powered prosthesis to differentiate between standing, walking and sitting modes. Other studies [6, 7] conducted on mechanically passive devices have shown potential for using electromyography (EMG) from residual limb muscles to perform intent recognition over different terrain types. To the authors' knowledge, no studies have demonstrated an intent recognition system for a powered knee-ankle prosthesis that works across multiple locomotion modes.

While both EMG and mechanical sensors are potentially useful for intent recognition, the statistics (or features) of these signals change throughout gait cycle [8]. Therefore, it may be beneficial to capture the sequence or the time history of the signals over time. One efficient algorithm that uses time history is a Hidden Markov Model. It combines current observation information with past information in the form of priors from the previous time step to predict a discrete output variable. Hidden Markov Models assume stationary signals, and thus a Dynamic Bayesian Network (DBN) [9] was used which is similar to a Hidden Markov Model, but relaxes the stationary assumption. DBNs are useful for integrating time series information over time. The DBN was constructed to have a different underlying sensor model based on gait phase. This type of classification using time history was implemented in order to utilize the information throughout the gait cycle for locomotion mode classification.

The goal of this study was to develop an intent recognition system for transfemoral amputees across multiple ambulation modes (level-ground walking, ramp ascent/descent, and stair ascent/descent). First, intent recognition was evaluated for the stair trials and the ramp trials separately. Then, classification performance for separating both stairs and ramps were evaluated and the benefits and disadvantages of each are discussed. For all these analyses, an intent recognition strategy using a DBN was used to incorporate time history information along with a combination of EMG and mechanical sensor information. EMG information precedes movement and may be helpful for predicting upcoming transitions [6], while mechanical information reacts to movement and is stable over time and may help to stably classify the steady-state locomotion.

II. METHODS

A. Experimental Protocol

Four transfemoral persons with a transfemoral amputation (three males and one female) completed the following experiment that had been approved by the Northwestern University Institutional Review Board. Nine muscles sites on the residual limb of the amputee were recorded by surface EMG including: semitendinosus, biceps femoris, tensor fasciae latae, rectus femoris, vastus lateralis, vastus medialis, sartorius, adductor magnus, and gracilis. Three of the amputees wore custom skin-fit suction sockets with embedded stainless-steel dome electrodes placed over the muscle sites. One amputee wore reusable, low-profile, self-adhesive silver-coated carbon electrodes (Arrowhead Medical Resources) underneath his liner and home socket. On two of the subjects, a single EMG channel was lost or discarded due to noise.

All amputees wore a powered knee and ankle prosthesis designed by collaborators at Vanderbilt University [10]. The prosthesis was attached to the amputee's socket and aligned by a certified prosthetist at the Rehabilitation Institute of Chicago. Each patient had experience on the robotic leg walking on level ground, walking on a ramp with a 10 degree slope, and ascending and descending a set of stairs using reciprocal gait (see Fig. 1.) The impedance parameters for the knee and ankle were empirically tuned for each locomotion mode as described previously [11]. State machine based control that has been presented previously was used and impedance parameters for the robotic leg for walking [5], stairs [4], and ramps [12] were tuned to each patient.

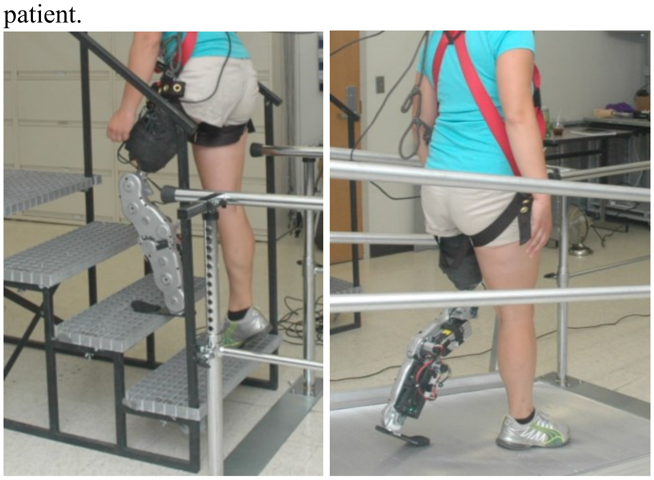

Fig. 1. Transfemoral patient walking on the Vanderbilt powered knee/ankle prosthesis for stair climbing (left) and ramp descent (right).

Patients completed 20 repetitions of two circuits. In the first circuit, the patient walked on level ground, transitioned to ramp ascent, transitioned to level walking, turned around, walked back to the ramp, transitioned to ramp descent, transitioned to level walking, continued level walking and stopped to end the trial.. The second circuit was the same as the first except the ramp was replaced with a four–step staircase. An experimenter transitioned the prosthesis between the different locomotion modes at heel contact or toe off.

B. Signal Processing and Classification

EMG signals were sampled at 1000 Hz and mechanical sensors were sampled at 500 Hz. A custom built EMG system was used to record EMG which included a hardware band-pass filter between 20 and 420 Hz. Thirteen mechanical sensors (six axis inertial measurement unit, axial load, and position, velocity, and motor current for both the knee and ankle) along with the nine EMG channels were used for classification. The load cell was low pass filtered at 20 Hz. The locomotion modes and gait cycle phases were also recorded.

Data were segmented into analysis windows of 300 ms at eight different points throughout the gait cycle: heel strike, 25/50/75% of stance phase, toe off, and 25/50/75% of swing phase. Mean, standard deviation, maximum and minimum values were extracted as features from each window for the mechanical sensors. Mean absolute value, zero crossings, slope sign changes, waveform length and the first two autoregressive coefficients of a sixth order autoregressive model were extracted for EMG signals [6]. The full set features from the EMG and mechanical sensors were concatenated and used for classification.

Time history based classification was implemented using a dynamic Bayesian network (DBN) [9]. A Two-Timeslice bayesian network was used which means that at any point in time, the output class can be calculated from current observations and the priors from the previous step. This is the Markov assumption which states that future decisions are conditionally independent of past states given the present state.

The DBN used Bayes law to calculate the maximum a posteriori (MAP) estimate (Eq. 1), which was the class with the maximum posterior probability $p(C|\vec{x})$). The MAP estimate is a combination of past information in the form of a prior and current information (the likelihood). The prior ($p(C)$) was the probability based on past information of being in any of the classes. Thus the MAP estimate was calculated from Eq. 2. where $p(\vec{x}|C)$ is the likelihood probability, $p(\vec{x})$ is the observational probability, and $\hat{C}_{MAP}$ is the MAP estimate.

$$\hat{C}_{MAP} = \arg\max(p(C|\vec{x})) = \arg\max\left(\frac{p(\vec{x}|C)p(C)}{p(\vec{x})}\right) \quad (1)$$

The priors for each step were calculated based on equation 2, which is a matrix multiplication of the previous step's posterior probabilities ($p(C|x)_{t-1}$) and a transitional probability matrix (ϕ). The transitional probability matrix (ϕ) was learned from the training data and describes the probability of transition between any two activity modes.

$$p(C)_t = p(C|x)_{t-1} * \phi \quad (2)$$

At any given time t, the current features and gait phase were known. The gait phase determined the feature model used at any time step. Eight models were used corresponding to the pre-defined eight points during the gait cycle. At any given time, a model calculated a set of likelihood probabilities from the feature information, and prior probabilities were propagated from the previous time point. Posterior probabilities were calculated based on Eq. 1. The class with the maximum posterior probability was chosen for that time step. The posterior probabilities were then multiplied by the transitional probability matrix (Eq. 2.) and propagated to the next time step sequentially in time through the gait cycle. This allowed for information to be propagated throughout the gait cycle to increase the information available at the critical transition points (heel contact and toe off).

C. *Performance Evaluation*

Classifier evaluation was performed using leave-one-out cross validation with all circuit trials collected for each patient. For overall system evaluation, errors were divided into transitional error and steady-state error. Transitional error was the percentage of transition steps misclassified, while steady state error was the percentage of steps not occurring at a transition that were misclassified. While multiple points in the gait cycle were used to implement the time history strategy, classifier performance was evaluated exclusively in terms of decisions at heel contact and toe off as these are where transitions between modes are initiated.

Intent recognition was tested on the ramp trials and separately on the stairs trials to evaluate performance for each ambulation mode. Next the performance of an intent recognition system with all five locomotion modes (level-walking, ramps and stairs) was evaluated. To further reduce recognition errors, two additional configurations were tested. Since the prosthesis response and impedance parameters during ramp ascent was very similar to the prosthesis response during the level-walking, the first of these configurations combined these two modes into one class (i.e. ramp ascent steps were relabeled as level-walking). The second configuration evaluated was suitable to be used in combination with a separate slope estimator that has been presented in previous work [12] with the Vanderbilt knee/ankle prosthesis. For this configuration both the ramp ascent and descent steps were relabeled as the level-walking mode; allowing the intent recognition algorithm to only have to separate three locomotion modes (level walking, stair ascent and stair descent). Statistical analysis was performed for both transitional and steady-state error separately using a 1-way ANOVA with subject as a random factor and locomotion mode as a fixed factor.

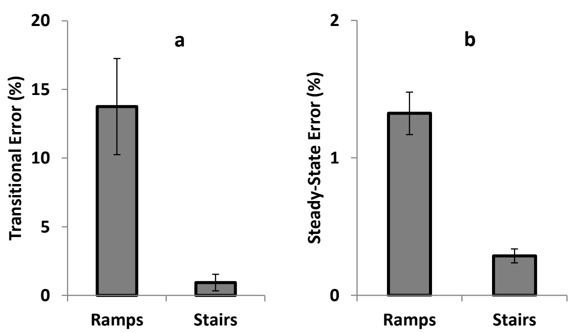

Fig. 2. A) Transitional and B) steady-state error for the separate ramp and stair intent recognition systems. Data are averages of four subjects and error bars represent +/- 1 SEM.

III. Results

A. *Analysis of Ramps and Stairs Separately*

The intent recognition performance was evaluated separately for ramps and stairs and results showed that stairs had significantly lower ($p<0.05$) error rates for both transitional and steady-state steps than ramps (Fig. 2). For the ramp intent recognition system 33% of the misclassifications were between level walking and ramp ascent, 64% were between level walking and ramp descent and 2% were between ramp ascent and descent. For stair the stair intent recognition system, 83% of the misclassifications were between level walking and stair ascent, while 17% of the misclassifications were between level walking and stair descent. Error rates were higher during transition steps than during steady-state steps (Fig. 2). Ramp transition steps (i.e. steps between level ground and ramp ascent or descent) were nine times more likely to have a misclassification than a steady-state step.

B. *Effect of Classifier Configuration*

By training the intent recognition system to identify all five locomotion modes (Fig. 3), overall error rates were similar to the ramp classification rate shown in Fig. 2. When the system was trained to recognize four modes (i.e. ramp ascent and level walking combined into one class), error rates for transitional steps were significantly ($p<0.05$) reduced, and error rates for steady-state steps were reduced, but not significantly (Fig. 3). Finally, when the system was trained to recognize only three modes (i.e. ramp ascent, ramp descent and level walking combined into one class), the transitional error was significantly reduced by 92% ($p<0.01$) and steady-state error was reduced by 86% ($p<0.01$) compared to classifying all five locomotion modes

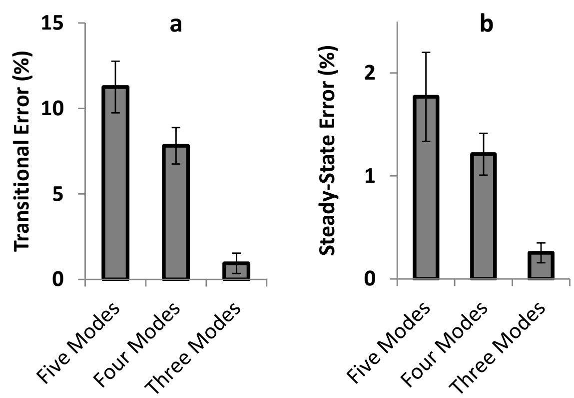

Fig. 3: A) Transitional and B) steady-state error for three different classifier configurations. Configurations included all modes as separate classes (Five Modes), ramp ascent relabeled as level walking (Four Modes), and both ramp ascent and ramp descent relabeled as level walking (Three Modes). Data are averages of four subjects and error bars represent +/- 1 SEM.

as separate classes. This indicated that a large portion of the errors for both transitional and steady-state were due to ramp misclassifications and only a small amount were due to stair misclassifications.

IV. Discussion

This study found that ascending and descending ramp were more difficult to classify than ascending and descending stair for both transition and steady-state steps (Fig. 2). It is likely that this was because ramp steps have signal patterns that are more similar to level-walking steps, while stair steps have patterns that are different from both level-walking or ramp steps.

The intent recognition system trained with all five locomotion modes as separate classes had relatively high (11.3%) transitional step errors even when using a combination of neural and mechanical sensor information. By relabeling the ramp ascent mode to level walking, transitional error and steady-state error was reduced by 31%. With this configuration, the intent recognition system would keep the prosthesis in level-walking mode during ramp ascent. For the four amputees tested in this study, this four-mode control scheme is valid since the tuned impedance parameters were very similar between level-walking and ramp ascent modes for each subject. Thus a configuration with ramp ascent trained as walking would not likely be noticed by the amputees and be implemented with fewer overall errors. The three-mode system resulted in the least amount of errors; relabeling both ramp ascent and descent to level walking reduced transitional step errors to 0.9% and steady-state errors 0.3%. This effectively removed all ramp misclassifications without increasing stair misclassification rate which is beneficial, but at the cost of only being able to recognize ramp modes as level walking. This three-mode strategy could be used in combination with a slope estimator such as the one presented previously by Sup [12] by adding an accelerometer to the foot. While the ramp ascent and level-walking modes have similar impedance parameters, a slope estimator is necessary as the ramp descent mode is substantially different. Without a slope estimator, some amputees might find it uncomfortable to be in the level-walking mode when descending ramps. Another possible solution for the three-mode system might include adding a second stage classifier that separates out desired ramp mode(s) when the level-walking class is chosen. This strategy would take advantage of the low stair error rates while possibly lowering the ramp error rates.

All classifier configurations in this study used a combination of EMG data from patients' residual limbs and mechanical sensor information from the powered prosthesis. A fusion of multiple data sources such as this may be useful for intent recognition [6], and future work will consider the impact of each type of sensor on recognition accuracy. Additionally, an intent recognition system that incorporated the time history of each input signal was used to fuse information over the course of the gait cycle. The time history information was included in a DBN which combined information in a way that is similar to a hidden markov model or kalman filter in that relevance prior information is fused with current information to make a more likely prediction. This is the first time that these methods have been put together for powered prosthesis intent recognition. Future studies will include real-time testing to determine the viability of different intent recognition configurations and strategies for powered prosthesis control.

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